CHOOSING AN OBJECTIVE FUNCTION BASED ON MODELING CONSUMER PERCEPTIONS AND PREFERENCES

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Abstract

Many mathematical models deal with how best to provide service to consumers. In emergency police and ambulance services, in transportation services, in communications services, ultimately some objective is maximized. But what objective? To choose an objective we must first understand (1) how consumers perceive the various alternatives and (2) what are their preferences relative to the performance measures they use to judge systems. We present techniques to uncover the perceived performance measures that consumers use to select destinations and measure utility functions which capture their preferences relative to these dimensions. Empirical examples are given in the context of non-grocery shopping trips. Further, we demonstrate how a consumer-oriented approach is used to choose an objective function for a dial-a-ride routing and scheduling algorithm.

Dial-a-ride is a computer-dispatched mini-bus transportation system which provides door-to-door service on demand. In this system, much like a taxi system, a consumer requests service by phone, is picked up from his origin and is taken to his destination. Dial-a-ride differs from a taxi because it is a shared-ride system, hence the consumer can expect deviations enroute to pick up and drop off other people. In this system, the computer controls which vehicle serves which passengers and also the order in which passengers are served. The general objective is to provide quality service without a major operating deficit. But how does this translate into a specific objective function for the computer to optimize?

Consider the design of dispatching strategies for police service. Preemptive service is an important consideration. For example, suppose a robbery is in progress at the corner of First and Main Streets. Should we dispatch the nearest available free unit, or should we dispatch an even closer unit which is performing what amounts to a routine inquiry? (We might then dispatch the free unit to continue the inquiry.) To set such strategy we need good probabilistic models which model the potential locations of both vehicles as well as their times in service and probable future demands on service? (Many such models exist, see Larson[26] or Oswald [34].) But even with good explanatory models and good optimization strategies we must still know what objective to optimize.

Examples of optimization abound. For example, Michandani[33] deals with the location of fixed facilities on stochastic networks, Handler[14] deals with crew scheduling for the airlines, Marks[31] with the optimization of water quality, Gardner, Little, and Gabby[11] with the sequencing of traffic signals, and so forth. Each of these efforts shares the common bond of optimizing some objective function. But which objective function? What performance measures should we include? What should the function look like? What parameters represent our priorities? This paper addresses these three questions by suggesting an adaptation of our experience in using marketing research methodologies which go directly to the ultimate beneficiary of these optimizations, the consumer. Empirical examples are given from dial-a-ride algorithms and from the design of shopping centers. Let us begin with a short review of techniques which are now used to choose objective functions.

Existing Objective Functions are Based on the Judgments of Managers and Analysts

The purpose of most optimizations is to have some impact on real policy decisions and strategies. But impact implies consequences, and it is ultimately the policy makers (whom we shall call managers) and their consultants (whom we shall call analysts) who must bear the responsibility for the consequences. Thus, most objective functions come either formally or informally from either the managers, the analysts, or both. The informal techniques are simple. Either the analyst uses his experience and judgment, or he consults first with the manager, or he and the manager together choose the objective, or they both consult an expert in the field. The choice depends on the time scale, the importance of the problem, and the sensitivity of the solution to the selection of an objective.

More and more, analysts are formalizing the process. Much theoretical and practical work has been done in a field known as multiattribute utility theory. (For an excellent review of this literature see Farquhar[7].) These techniques represent a formalization which expresses a manager's preferences in mathematical form. Based on fundamental normative axioms (von Neumann and Morgenstern[42]) and on identifiable independence properties (Fishburn[8,9], Farquhar[7], Kenney[20,21] and Kenney and Raiffa[24]), functional forms are identified which rank alternatives by combining performance measures into a single measure of goodness. These functions are then parameterized, with or without the aid of a computer (Sicherman[37]), by in-depth interviews with the manager. In addition, the theory provides an ability to collapse many related measures into aggregated performance measures. (See Ting[39] and Ellis and Kenney[6].) Examples of the use of multiattributed utility theory are the siting of Mexico City's airport (Kenney[19]), the siting of nuclear power plants (Kenney and Nair[23]), in blood banking (Bodily[27]), in air quality control (Ellis and Kenney[61]), and in medical decisions (Krischer[25]). Finally, recent work has effectively extended multiattributed utility theory to the case when the preferences of more than one manager must be combined. This theory combines the utility functions of each member to form a group function. (This is possible despite Arrow's impossibility theorem[1] because the functions are cardinal rather than ordinal. See Kenney and Kirkwood[22] and Bodily[3].)

Discussion: Whether formally or informally, the selection of an objective function is made by the man-

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agers and analysts. This is only right since they must bear the responsibility. We do not propose to override their judgment, because no matter what technique is proposed to aid in the selection of an objective, the managers must remain in control. Instead, our models serve to provide insight. They do not replace the manager who must make both our methodology and the optimization models serve him. But if we leave the manager and the analyst in control, what purpose can our techniques serve? Currently the manager and the analyst must make educated guesses as to what best serves their clientele. While some models are insensitive to these choices, others are not. In fact, entirely different decisions can often result from minor changes in objectives. In the dial-a-ride example, we may posit that the consumer wishes service with a minimum expected total trip time. But what if most consumers prefer more reliable service even if the service has a longer expected trip time? The former hypothesis implies an objective function which is linear in travel time and wait time, the latter implies a non-linear function, perhaps quadratic. But we may not even have the appropriate performance measures! Perhaps our consumer wants more personal or more comfortable service and would rather we spend our resources improving these dimensions. Without the proper performance measures and objective function the analyst's optimal decision may not satisfy the consumer. Thus, what we propose is not a new way to select objective functions, but rather a way to insure that objective functions indeed represent the manager's qualitative goals. The only way to do this is to consider consumer preferences explicitly. Properly measured, consumer preferences provide important diagnostics to guide managers and analysts in the selection of appropriate objectives.

Consumer Perception and Preference Measures Aid Managers in the Selection of Appropriate Objective Functions

The problem of choosing the right objective function is similar to problems in marketing. In marketing the task is to choose a product or service that will attract users. In the design of public services, the task is to design a service that fulfills the fundamental needs and desires of the consuming public. For example, demand for transportation is derived from fundamental travel needs; demand for police service is derived from a fundamental need for public safety; and optimal hospital location and ambulance dispatching strategies are optimal only in the sense that they serve the health needs of the community. Thus, to select objective functions we can draw on recent developments in marketing that explicitly measure (1) how consumers perceive public services and (2) what consumers' preferences are relative to tradeoffs among the perceived attributes of the services. For example, Hauser and Urban[16] developed methodologies for services such as health care delivery, education programs, financial services, and transportation systems. For systems analysis we will use the perceptual methodologies to identify performance measures and the preference methodologies to identify the form and parameters of the objective functions.

In addition, related methodologies can use the measures of consumer preference to identify segments of the population with different preferences. For example, suppose we were setting the optimal temperature of a cup of tea. Suppose half the population likes tea at 32°F (iced tea) and the other half likes tea at 104°F (hot tea). If we select an average temperature to satisfy the population, we would select 68°F. But this is simply lukewarm tea! Similarly, if we select an objective function for dial-a-ride service based on average tradeoffs among travel time and cost, we may satisfy no one!

Finally, once we have preference functions for consumers, we can predict consumer behavior.* The purpose of this prediction is twofold. First, by testing situations where consumers do have a choice, e.g., transportation mode choice, we can assess the accuracy of our models (Hauser[15]). Second, by predicting for situations where consumers do not have an explicit choice, e.g., hospital location, we can provide further input to the manager and help assess public reaction to his decisions.

We begin with the selection of performance measures.

Performance Measures are Based on Consumer Perceptions

Although we must ultimately select quantifiable measures representative of a random sample of the population, we instead begin with qualitative techniques on extremely small samples. These qualitative techniques insure that (1) we do not miss unexpected important measures and (2) that we can phrase later more exacting questionnaires in words that consumers normally use. Qualitative techniques include expert opinion, open-ended questionnaires (which favor articulate and fervent consumers), citizens groups, intercept interviews, and focus groups. Focus groups (Levy[28]), in which 6-8 consumers are encouraged by a moderator to discuss their feelings about potential systems, appear to be the most productive and most representative of the population. The output of these qualitative studies is a set of attributes which describe as completely as possible how consumers perceive the public services in question. For example, Figure 1 gives a list of 16 attributes found to be important in evaluating the "attractiveness" of shopping centers. (See Stopher and Watson[38] for details of their development.)

1. Layout of store
2. Ease of returning or servicing merchandise
3. Prestige of store
4. Variety or range of merchandise
5. Quality of merchandise
6. Availability of credit
7. Reasonable price
8. Availability of sales items ("specials")
9. Free parking
10. Store located in a compact area
11. Store atmosphere (heating, cooling, noise, crowds, etc.)
12. Ability to park where you want
13. Shopping center atmosphere
14. Courteous and helpful sales assistants
15. Availability of a specific store
16. Number and variety of stores

Figure 1: Sixteen attributes found to be important in evaluating the "attractiveness" of shopping centers.

We must now measure a random sample of consumers. (In some cases this may not be feasible, so we would select a choice-based sample. See Lerman, Manski, and Atherton[27].) In the shopping center case, we measured (1) consumer ratings on the 16 attributes for each shopping center in the consumer's choice set and (2) consumer preference rankings for the shopping centers based on the assumption of their being equally accessible. In addition, actual distance from home to each center, demographics, and various psychographics were measured. Figure 2 gives an example of the measurement scales for the attributes and for preference.

*In some cases, it is necessary to use addition models to link preference to probabilities of choice. See Hauser and Urban[16].

If all the following shopping centers were equally easy to get to, which of them would you prefer to shop at for the goods you came to buy?

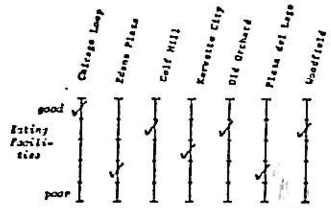
Please indicate your order of preference by placing a number beside each center. Start with number 1 for the most preferred shopping center, number 2 for the second most preferred, and so on down to the least preferred shopping center.

Please rank all the shopping centers.

Chicago Loop	[ ]
Edens Plaza (Wilmette)	[ ]
Golf Mill Shopping Center	[ ]
Korvette City (Dempster & Kostner)	[ ]
Plaza del Lago	[ ]
Old Orchard	[ ]
Woodfield	[ ]

In this question, we would like you to rate each of the shopping centers on these characteristics. We have provided a range from good to poor for each characteristic. We would like you to tell us where you feel each shopping center fits on this range.

For example:



Please do this for all the shopping centers on all the characteristics.

Figure 2: Measurement scales for (a) preferences and (b) perceptions of the attributes.

If after analysis of the data we find that all attributes are important to the choice process, we might be tempted to quantify each and use them in our objective function. But experience indicates that it is useful for managerial insight to reduce the set to a more tractable number of attributes. To do this, one can use information theory (Boyle[2], Gallagher[10]) to select the attributes which best explain preference, or one can use multidimensional scaling (Green and Wind[12], Carroll[5]) to estimate surrogate measures from statements by consumers about the relative similarities of existing services. We have found a third technique, factor analysis, (Rummel[36]) most tractable. For example, Figure 3 gives a factor loadings matrix obtained by analyzing the 16 scales across 500 individuals and 7 shopping centers. Interpretation of this table reveals that the attractiveness of shopping centers can be effectively represented by four underlying perceptual dimensions: variety, shopping satisfaction, parking, and cost/value. Thus, if we were selecting an objective function to guide our design of a shopping center, we would select quantifiable attributes chosen to best represent these four dimensions. Examination of which attributes load together on a factor guides us in this selection. Consumer measurement techniques such as conjoint analysis (Tversky[40], Green and Wind[13]), tradeoff analysis (Johnson[18]), and direct consumer utility analysis (Hauser and Urban[17]) would then be used to link the quantifiable attributes to the perceptual dimensions.

The output of the perceptual analysis is a set of measures which parsimoniously describe how consumers perceive the services. For systems analysts this serves as a guide to select the appropriate performance measures for the objective function. But are all these measures important in choice? And if they are, what should the objective function be? To answer these questions we turn to preference analyses.

Objective Functions Are Based on Consumer Preferences

Many optimizations deal with linear or quadratic objective functions. For example, consider linear programming, quadratic programming, integer programming, and linear-quadratic optimal control problems. We will continue with the shopping center example to illustrate how to select a linear objective function and then give an example of a computer dispatching algorithm that is now using a consumer-oriented quadratic objective function.

Attributes	Variety	Satisfaction	Parking	Price/Value
1. Layout of store	.267	.583	.200	.156
2. Return and service	.095	.528	.255	.343
3. Prestige of store	.338	.822	-.058	-.001
4. Variety of merchandise	.665	.327	-.165	.309
5. Quality of merchandise	.357	.810	-.074	.037
6. Availability of credit	.159	.337	.049	.487
7. Reasonable price	.067	-.063	.113	.599
8. "Specials"	.223	.074	.008	.739
9. Free parking	-.150	.068	.811	.043
10. Center layout	.030	.308	.560	.074
11. Store atmosphere	.080	.658	[illegible]	.034
12. Parking available	.145	[illegible]	.841	.103
13. Center atmosphere	.244	.694	.404	-.040
14. Sales assistants	.173	.560	.319	.147
15. Store availability	.619	.320	.034	.204
16. Variety of stores	.829	.288	-.173	.160

Figure 3: Factor analysis of the attributes that consumers use to evaluate the "attractiveness" of shopping centers.

If we are to use a linear objective function, we need to estimate which weightings of the performance measures best capture consumer preferences. To do this we must use either the rank order preferences collected in our questionnaire or, if appropriate, actual choice. Suppose we use the preferences. In this case we use a preference model which estimates the weights to best link the performance measures to the rank order preference. There are a number of techniques to do this estimation, including least squares preference regression (Urban[41]), monotonic preference regression (Johnson[18a]), and logit analysis (McFadden[30]). Hauser and Urban[16] found that for health care delivery each method gave similar weights and predictions. We will give an example only of logit analysis and refer the reader to the references for the other techniques. The reader is cautioned that (1) the Hauser-Urban tests have not yet been performed for other service categories, (2) there are other techniques such as conjoint analysis which have not been tested relative to these techniques, and (3) there is some evidence that nonlinear preference functions give better predictions of aggregate market shares. (See Hauser and Urban[17].)

In the logit model we assume that the true consumer objective function, $f_t(\cdot)$, can be represented by a weighted sum of the performance measures plus an additive error term. I.e.

$$f_t(\cdot) = \sum_k \lambda_k \cdot X_{ijk} + \varepsilon_{ij}$$

where λ_k are the weights to be estimated and X_{ijk} are the levels of the k^{th} performance measure for individual i and for service j. ε_{ij} is the error term. If we assume that the error term is independent and indentically distributed across individuals as a Weibull random variable, we can calculate that the probability, P_{ij}, that individual i will rank service j first given he uses $f_t(\cdot)$. (This is a probability rather than certainty because of the error term.) This probability is given by:

$$P_{ij} = \exp(\sum_k \lambda_k \cdot X_{ijk}) \Big/ \sum_\ell \exp(\sum_k \lambda_k X_{i\ell k})$$

Logit then uses maximum likelihood techniques to estimate the optimal weights. In the shopping center example, analysts would either use the factor scores obtained in the perceptual analysis or the quantifiable attributes chosen to represent these perceptions. As an illustration, we estimated the optimal weights if the factor scores were used as performance measures. These weights are given in Figure 4. All weights were significant at the 5% level and hence all should be included in the objective function. Examine Figure 4 and suppose that you are the manager of a new shopping center. You are trying to decide how much land to allocate to stores and how much to allocate to parking. Given that the weight for variety is over 16 times the weight for parking, how might you allocate this land? (Remember that the variety of the stores and the availability of specific stores correlates with the performance dimension of variety.) Of course, to make the real engineering decision, you must use conjoint measurement or related techniques to link the factor scores to engineering variables such as the number of stores in each category and the number of parking places. Furthermore, the exact allocation would be set with an optimization model. But this example does illustrate the importance of selecting an appropriate objective function.

		linear weight
X_1:	variety	.33
X_2:	shopping satisfaction	.39
X_3:	parking	.02
X_4:	price/value	.26

$$\text{objective function} = .33X_1+.39X_2+.02X_3+.26X_4$$

Figure 4: Weights selected for an optimal linear objective function through the analysis of consumer preferences.

An Example: Dial-a-Ride Computer Routing Algorithm Uses a Consumer-Based Objective Function

In a dial-a-ride system the purpose of a computer routing algorithm is to assign passengers to vehicles and to determine the route which the vehicle follows in serving those passengers. (For details of the algorithms see Wilson[43] and Wilson, Weissberg, and Hauser[44].) To assign passengers and to route vehicles the algorithm needs some criteria, i.e., an objective function. Previous operational experience indicates that users consider at least five aspects of service which the computer can affect. These are: (1) wait time -- the time between service request and pickup, (2) ride time-- the time between pickup and delivery, (3) total time -- the time between service request and delivery (actually the sum of (1) and (2)), (4) pickup deviation -- the difference between promised pickup time and actual pickup time, and (5) delivery deviation. Currently these five performance measures are being used by the algorithm, but research is underway to measure consumer perceptions, possibly to improve this set of performance measures.

The purpose of the dial-a-ride system is to provide superior transportation service to consumers. The purpose of the objective function is to insure that what the algorithm considers optimal is actually optimal in terms of consumer preference. Thus, for each potential assignment the algorithm first computes the estimated values of the performance measures for (1) each passenger already on board, (2) the passenger being assigned, and (3) a surrogate for future passengers. The assignments are then evaluated by using preference functions to compute each of these consumers' loss in "utility" resulting from the assignment. The algorithm chooses the assignment and routing which minimizes the total loss of "utility."

Originally the algorithm used a linear preference function (Wilson[43]), but operating experience indicated that consumers were willing to sacrifice average wait and travel time if they could get a more reliable service. This desire could not be satisfied with a linear utility function because linear functions always choose the routings with the smallest expected time no matter how unreliable this estimate is. For example, if the two curves in Figure 5 represent probability density functions for wait time, a linear function would choose the curve with the lowest expected wait time (curve b), even though reliability seeking consumers would prefer the more reliable curve (curve a). In terms of preference functions, this desire for reliability is equivalent to risk aversion and therefore implies that the preference function should be concave in each performance measure (Raiffa[35]). Since the algorithm essentially optimizes with an exhaustive search over potential assignments, the objective function must be computationally efficient. This constraint limits the objective function to be completely linear or to be a sum of univariate functions which are each quadratic in a performance measure. (Quadratic functions are computationally efficient because they are linear in their differentials, i.e., in incremental utility loss.) Fortunately, quadratic forms are concave and thus incorporate consumers' concern for reliability. When the more behaviorally sensitive functions were incorporated in the algorithm and service performance was predicted with Monte Carlo simulation, Wilson, Weissberg, and Hauser[44] show that the behavioral preference functions do indeed provide more reliable service.

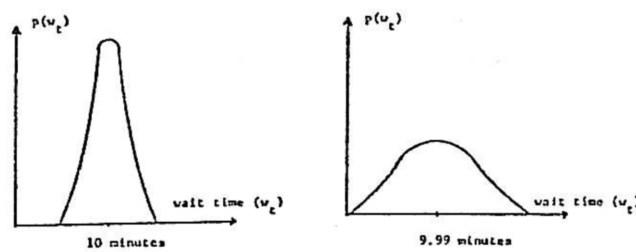


Figure 5: Relibale and unreliable probability distributions of wait time. (Reproduced from Wilson, Weissberg, and Hauser[47].)

At present, in actual system use, the parameters being used in the algorithm are set with judgments by analysts, planners, and managers. Work is now underway (Menhard[32]) to measure consumer preferences to provide direct specification of the objective function.

We present this example because it illustrates how systems analysts can directly incorporate consumer preferences into algorithms which control public services. In this case, service is improved with a consumer-oriented approach to selecting objective functions. We feel that this is indicative of even greater gains possible when consumer-based objective functions are used.

Discussion and Summary

Most of the mathematical analyses for modeling spatial and temporal processes have as their ultimate goal the optimization of an objective function. This paper has not dealt with how to model such processes, nor how to achieve an optimal system. Instead, it has dealt with the question of what is optimal. It is our feeling that in any practical application this question must be explicitly addressed because if it is not, modelers run the risk that their "optimal" system is far from what the public truly wants.

The purpose of this paper has been to briefly review techniques which can help modelers use market analyses to select objective functions. Such consumer-oriented objective functions are important in achieving goals for systems because they have performance measures that correspond to consumers' perceptions and parameters that correspond to consumers' preferences.

Together the shopping center and dial-a-ride examples indicate (1) that it is feasible to make the required measures and estimate the parameters, and (2) that such objective functions can readily be incorporated into computer optimization algorithms. For the details of attribute measurement, performance measure identification, and parameter estimation, we refer the reader to the references.

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